Hybrid Genetic Firefly Algorithm-Based Routing Protocol for VANETs

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ABSTRACT Vehicular Adhoc Networks (VANETs) are used for efficient communication among the vehicles to vehicle (V2V) infrastructure. Currently, VANETs are facing node management, security, and routing problems in V2V communication. Intelligent transportation systems have raised the research opportunity in routing, security, and mobility management in VANETs. One of the major challenges in VANETs is the optimization of routing for desired traffic scenarios. Traditional protocols such as Adhoc On-demand Distance Vector (AODV), Optimized Link State Routing (OLSR), and Destination Sequence Distance Vector (DSDV) are perfect for generic mobile nodes but do not fit for VANET due to the high and dynamic nature of vehicle movement. Similarly, swarm intelligence routing algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) routing techniques are partially successful for addressing optimized routing for sparse, dense, and realistic traffic network scenarios in VANET. Also, the majority of metaheuristics techniques suffer from premature convergence, being stuck in local optima, and poor convergence speed problems. Therefore, a Hybrid Genetic Firefly Algorithm-based Routing Protocol (HGFA) is proposed for faster communication in VANET. Features of the Genetic Algorithm (GA) are integrated with the Firefly algorithm and applied in VANET routing for both sparse and dense network scenarios. Extensive comparative analysis reveals that the proposed HGFA algorithm outperforms Firefly and PSO techniques with 0.77% and 0.55% of significance in dense network scenarios and 0.74% and 0.42% in sparse network scenarios, respectively.

INDEX TERMS Firefly optimization, genetic algorithm, routing, swarm intelligence, VANET.

I. INTRODUCTION

Vehicular Adhoc Networks (VANETs) can be used as a driver's assistance for communication and coordination among each other that will minimize the critical situation in V2V communication, e.g., random braking, obstacles, accidents on the road, bumper to bumper jams, random increase in speed, pathways for emergency vehicles like fire, police, and ambulance. Along with these preventive applications, VANETs are also useful for comfort applications to drivers and passengers, e.g., multimedia applications, internet

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connectivity, weather forecast, and infotainments during drives. Crash Avoidance Matrices Partnership (CAMP), Advance Driver Assistance System (ADASE), FLEETNET, and CARTALK are some of the famous applications that are developed by various automobile manufacturers and governments through public-private partnerships [1].

Figure 1 illustrates the typical VANET structure, but VANET also has some issues and challenges, like multipath fading and road obstacles, traffic congestion, random change of vehicle speed and its mobility, road topology, traffic diversion model, driver's unpredictable driving behaviour, etc. VANET mobility is not as same as that of Mobile Adhoc Network (MANET). In VANET, the vehicle strictly follows

the rules of traffic laws, and this makes node movement too complex. There are many limitations in VANET, and these challenges must be solved to provide reliable services in a network. Hence, reliable and stable routing is one of the major issues in VANET. So, accurate methods in realistic traffic environments also need to be implemented. The vehicle's dynamic behaviour and high mobility speed make routing in VANET even more challenging. Hence, the selection of the VANET routing protocol is the most challenging aspect and has been categorized into five different categories depending on their routing properties.
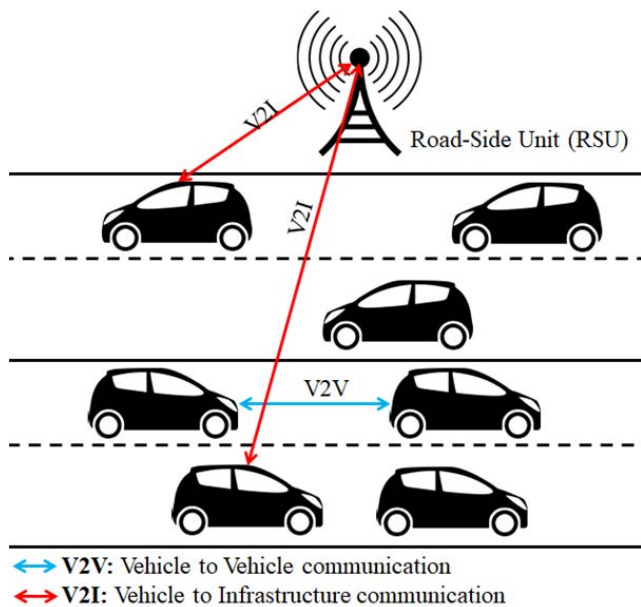

FIGURE 1. VANET structure.

The packet forwarding technique is used in topology-based routing protocols. It uses link-based information of the nodes in that network. The topology-based protocol is further divided into three other topologies as per the routing behaviours and these are reactive, hybrid, and proactive. These are used in VANET and suits only for specific VANET network scenarios. The Ad-hoc On-demand Distance Vector (AODV) [1] and Dynamic Source Routing (DSR) [2] protocols are used mainly in reactive topology-based routing. The critical analysis of AODV, DSR, and Optimized Link State Routing (OLSR) presented for highway and realistic city scenarios [3]. AODV and OLSR protocols are also selected for performance analysis with the newly devised algorithm as it is suitable for dense as well as sparse VANET network scenarios. Other urban-based modified AODV protocols were proposed [4] but they have their limitations and are only suitable for urban-based VANET network scenarios. Another routing protocol is cluster routing where packs of vehicles share the same properties in VANET scenarios. The single node is considered as the head within the cluster and broadcasts the information to all other nodes of that network. The same is proposed in platooning of vehicles in VANET [7].

One of the VANET routing protocols is broadcast. In this routing technique, the information is disseminated as a flood of data packets to all other nodes in the entire network. This is best used for information sharing at the time of emergencies, climate and weather forecasts, road damage in upcoming routes, and other urgent announcements. The DEnsity aware reliable broadCAsting protocol (DECA) and Distributed Vehicular broadCAST protocol (DV-CAST) are also proposed that show significant impact in VANET for broadcasting-based routing [8]. However, Geo-Casting routing works on a position-based approach to send multicast data packets in a network. The basic concept it uses to send data packets from one source to many destinations of the same geographical area is called Zone. The other geo-cast-based protocols are Geo-CAST Routing for Query Dissemination in VANET (DG-CASTOR), Inter-Vehicle Geo-cast (IVG), and Distributed Robust Geo-cast (DRG) [9]. All these geo-cast routing protocols worked best at the zone of relevance in VANETs. But none of them integrated the genetic approach with firefly swarm intelligence to analyze the performance based on transmission time [10].

It is found that no metaheuristic-based routing technique performed efficiently for sparse, dense, and real city traffic scenarios at the same time [10]. Particle Swarm Optimization (PSO) works fine in city-based scenarios for dense networks whereas Ant Colony Optimization (ACO) is best suited for highway-based scenarios in sparse networks. Also, the majority of metaheuristics techniques suffer from premature convergence, being stuck in local optima, and poor convergence speed problems. Hence, in this paper, a hybrid algorithm is proposed that has the features of the Genetic Algorithm (GA) along with the properties of the Firefly routing algorithm. The proposed protocol is capable to mutate as per the needs of the VANETs to achieve fast and reliable routing in different highway-based scenarios.

The main contributions of this paper are as follows.

1. Hybrid Genetic Firefly Algorithm-based Routing Protocol (HGFA) is proposed for faster communication in VANET.
2. To achieve faster and reliable routing, features of the Genetic Algorithm (GA) are integrated with the Firefly algorithm.
3. The proposed HGFA is validated on both sparse and dense network scenarios.

The remaining paper can be organized as follows: Section II discusses the related work. The proposed model is presented in Section III. Simulation and experimental results are presented in Section IV. Section V concludes the paper.

II. RELATED WORK
A. BACKGROUND INFORMATION
Recently, many researchers have utilized nature-inspired algorithms for selecting the optimal routes in VANETs. Some commonly used nature-inspired algorithms are PSO, flower pollination algorithm, GA, artificial bee colony algorithm,

ACO, Cuckoo search, bat algorithm, and Firefly Algorithm (FA). In [2], a Genetic Algorithm (GA) was integrated with the Ant Colony Optimization (ACO) technique called GAACO was proposed for optimal route selection in VANETs. GAACO, GA, and ACO were implemented and tested for VANET performance. ACO was used for efficient routing in VANET traffic scenarios that proved better only with 0.25% of significance in transmission delay. The natural behavior of ants was used to find the shortest path from source to destination through a pheromone trail. GAACO reduced the overall delay and increased packet data delivery. It fits the highway traffic scenarios but has some challenges on urban city traffic because of the huge density of nodes. In [7], ACO was deployed with a preemptive traffic light algorithm. The platooning technique was applied to optimize the VANET routing in city traffic scenarios. However, it is not capable of sparse network environments.

In [16], the Grey Wolf optimization algorithm was proposed that works on a clustering-based technique for hunting. The social nature of wolves applied to gather themselves for a cluster. This makes them chase and hunt for prey in a cluster. The same clustering technique was incorporated for VANET scenarios for position and location, speed, direction, and other parameters. The limitation of [16] is that it only fits for a cluster-based environment.

In [17], the Bees optimization algorithm was used in VANET for safety information dissemination. The optimization algorithm worked on the idea that bees leave their hives in search of the nectar and travel until they found the food. Once they have found the food then this information is passed through a signal of the waggle dance. Using this concept, the Bees optimization technique broadcasts the information from the source node to other nodes accurately and timely. This algorithm is best suitable where road safety is a major concern and hence can prevent accidents. In [18], an optimized routing algorithm was proposed in VANET by designing route metrics and improving the genetic algorithm route optimization technique (IGAROT). Route metric was designed considering path loss, frequency, transmit power, and received signal strength to improve the communication in VANET. IGAROT was utilized to select the optimal paths.

In [19], a Reputation-based Weighted Clustering protocol (RWCP) was implemented for VANETs to maintain the cluster structure without any overhead. To stable the VANET topology, RWCP utilized various parameters like lane ID, number of nearby vehicles, position, and direction of vehicles. These parameters were optimized using the Multi-Objective Firefly Algorithm (MOFA) to reduce cluster overhead, improve packet delivery ratio, and improve cluster lifetime. In [20], Capacitated Vehicle Routing Problem (CVRP) was solved utilizing improved GA. This technique was aimed to reduce time, distance, and transportation costs.

B. LITERATURE REVIEW

In [27], a portable VANET routing protocol (PFQ) protocol was designed. Routing was achieved by using a fuzzy constraint Q-learning based on AODV. Fuzzy logic was utilized to check reliable routes by using multiple metrics, i.e., relative vehicle movement, path quality, and bandwidth. In case if position information is unavailable, PFQ can infer node movement using the information of neighbors. PFQ-AODV is also independent of lower layers. In [28], various routing protocols like OLSR, ZRP, and AODV were implemented on VANETs. It was observed that AODV achieved a better transfer rate at TCP level. OLSR achieved a significant reduction of overhead. The hybrid protocol ZRP achieved significant reduction in latency and enhancement in packet delivery ratio.

In [29], three routing approaches were designed, i.e., Control overhead reduction algorithm (CORA), Intersection dynamic VANET routing (IDVR), and cluster-based life-time routing (CBLTR) protocols. CBLTR enhanced the average throughput and route stability in a bidirectional segment scenario. IDVR improved the average throughput and route stability, and minimized end-to-end delay.

IDVR optimized the routes using current and destination location, and throughput values. CORA minimized the control overhead messages by optimizing the control overhead packets between cluster heads and its members. In [30], Greedy Perimeter Stateless Routing (GBSR)-B was designed for optimal selection of routes. It has successfully reduced the packet loss problems with GBSR and AODV protocols.

From the related work, it is found that the metaheuristics-based routing protocol has achieved better results than the competitive routing models. However, it is found that no metaheuristic-based routing technique performed efficiently for sparse, dense, and real city traffic scenarios at the same time. Also, the majority of metaheuristics techniques suffer from premature convergence [2], [11], [21], being stuck in local optima [7], [12], [13], and poor convergence speed [2], [7], [14], [15] problems. Therefore, to overcome these issues, a Hybrid Genetic Firefly Algorithm-based Routing Protocol (HGFA) is proposed for VANETs.

III. PROPOSED MODEL
A. SYSTEM MODEL
The background study and literature review were done to identify the research gap that has been used to resolve through this research. The problems identified in a present system of VANET routing are that the traditional and meta-heuristic algorithms are not able to fulfill the present routing challenges. Hence, this research presents a system model, which integrates genetic features with the firefly algorithm to resolve the routing issues in distinctive traffic scenarios. Further sub-sections focused on the communication model and methodology developed for this research work.

B. COMMUNICATION MODEL
In this research problem, vehicle-to-vehicle communication networks opted for routing optimization. Presently, VANETs are facing node management, security, and routing

problems in V2V communication. Intelligent Transportation System has raised the research opportunity in routing, security, mobility management in Vehicular Adhoc Networks (VANET). These research challenges are not suited for all types of network communication models. Therefore, this research work presents the proposed communication model that fits for sparse as well as dense network traffic scenarios in VANETs.

C. PROPOSED APPROACH TO OPTIMIZE THE VANET ROUTING IN DISTINCTIVE NETWORK SCENARIOS

In this approach, each node (vehicle) is considered a firefly. Hence, during the communication period, the frequency and intensity value of firefly flashes increases so higher the selection probability. The algorithm works to determine the shortest path between the source and destination nodes by calculating the route for the shortest path in-between. The proposed algorithmic approach is represented in Figure 2.
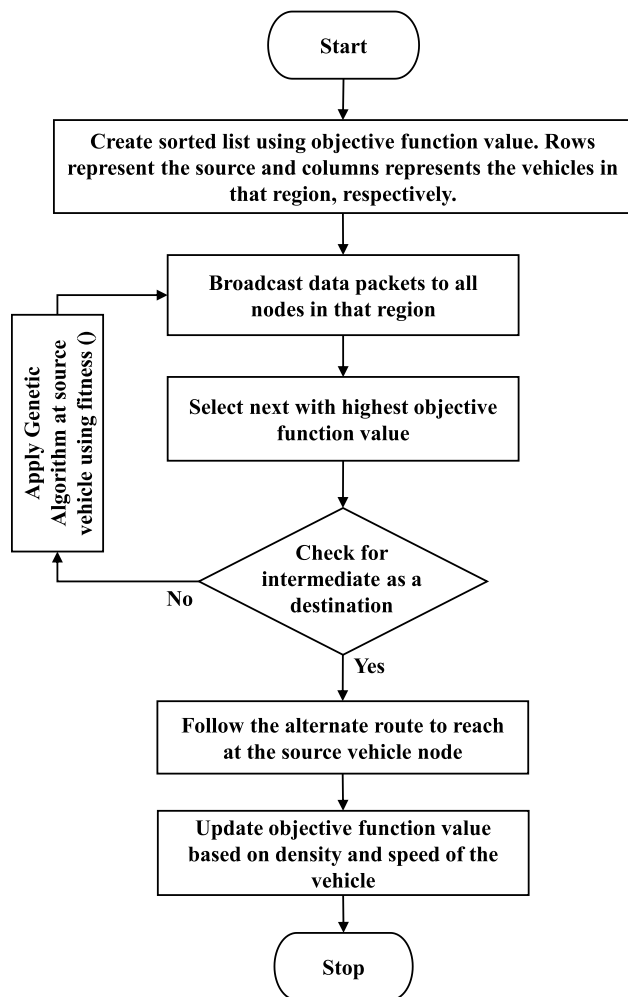

FIGURE 2. Flowchart of the proposed algorithm.

In this, the intensity value is based on the objective function value. The initial sorted list depends on the objective function value is created. Where it represents in rows and columns.

In this region, the column consists of many vehicles whereas the rows represent the source node. Then the GA algorithm is applied at the source node with fitness function to check the packet forwarded to other nodes for that region. Now the node with the highest value of the objective function is chosen as the next node. And further, browses for the intermediate node. Whether it is the destination node or not. If yes, then follow the reverse route to find the source node. Else, if not then follow the same steps to find the destination node. The updated objective function value depends on the speed of the vehicle and density. Hence, predicting the node's next position can be determined this gives us the possibility for making the smarter decision in finding the optimized route of the vehicle node.

The firefly algorithm works on the principle of attracting another firefly through its flashlight. Here, all the fireflies are assumed to be unisex [22]. The intensity of attraction is proportional to the distance among fireflies and the brightness of their flash. This means that the attraction is directly proportional to the brightness of the flash whereas inversely proportional to the distance. Hence, the movement towards each other depends on their attractiveness of each other. The objective function is entered in the sorted list.

Now the transmission needs improved for this object function and increase to maximum. The value of the objective function is calculated for every node. As the firefly algorithm works on the assumption that fireflies are unisex hence, they attract each other [23]. The attraction among the fireflies is based on the distance and brightness of the flies. When the brightness is high, and distance is low then the intensity of attraction will be more or else inverse of it. Therefore, depending on the intensity of attractiveness between them, one firefly can proceed ahead to the next firefly. The list is sorted for an objective function with a specific entry depending on the selection of the problem. Hence, for improvement in the network transmission, the value of the objective function needs to be increased at maximum level and it has to be calculated for every node as follows:

$$\xi r = \xi r_0 e^{-\psi} \tag{1}$$

Here, ξ shows brightness. ψ and ξr_0 define delay and initial value, respectively. Hence, the derived objective function is (mobility of the fireflies i^{th} firefly to next firefly k^{th} fireflies derived as) [24]. It can be computed as:

$$FF_{i+1} = FF_i + \xi e^{-\psi r^2} \left(FF_j - FF_i\right) + \omega \left(rand - \frac{\mu}{\mu_k}\right) \tag{2}$$

Here,

$$\omega = \omega \left(rand - \frac{\mu}{\mu_k}\right) \tag{3}$$

Here, ω shows free-flow speed. μ defines density. μ_k represents completely blocked traffic jam density. $\left(FF_j - FF_i\right)$ shows the Cartesian distance of ith and j^{th} firefly.

The distance taken at the stationary point for the derived object function as the vehicle node's speed may vary

and move in a random direction. For computing, the two-dimensional distance is calculated from the stationary point of the vehicle node. Hence, it is a Cartesian distance of these two points. The aim of this is to get the maximum value of the objective function for each node as there is dynamic mobility of nodes in comparison to other vehicle nodes.

GA is integrated with Firefly so that the Firefly algorithm can be improvised as per the need of the present problem of routing in sparse and dense network scenarios of VANET. GA here is used to initialize the initial population of the nodes and then whenever requires it is used to yield crossover for recombining of the initial state.

Algorithm 1 GA for Initial and Updated Swarm Position

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1.   T← 0 // for iteration
2.   Initialize S(T) //initial population
3.   Evaluate S(T) with computational parameters
5.   **While** T ≠ END
6.   **do**
7.   Recombine S(T) to yield crossover C(T)
8.   Evaluate C(T)
9.   Select S(T+1) from S(T) and C(T)
10.   T = T+1
11.   **End**
12.   **End**

Algorithm 1 shows steps of GA for initialization and updation of swarm positions. GA approach derived for firefly mainly focuses on the metrics like retransmission occurrence *NR*, the total time propagation *TP* and the coverage, i.e., *NC*. This function is defined as fitness function f(x). The network scenario will have time to wait and Time to Live which are T_{wr}, and *TTL* respectively. Here, *Twr* is the time when node v waits for retransmitting the data packets, and TTL is the time when the node will broadcast the data packets. They are both dependent on the probability of the adjacent node's network coverage., i.e., P_{nc}. The probability is computed through the total number of vehicle nodes, i.e., N_{np} which has received the data packets, and the total of neighbouring vehicle nodes, N_{vh} in that network coverage. Mathematically it can be computed as:

$$P_{nc} = \begin{cases} 0 & if\ N_{np} = 0 \\ 1 & if\ N_{vh} = 0 \\ \dfrac{N_{np}}{N_{vh}} & Otherwise \end{cases} \quad (4)$$

GA's fitness function is derived which has fitness value *x* for the function $f(x)$. The value is used for the next generation Gn, to determine the most possible parent. This fitness function f(x) has been already validated through NS2 in earlier research studies [25]. However, in our study, we have used this approach with the Firefly technique to devise a new approach that persists with the qualities of both in the proposed HGFA. Eq. (4) can be redefined as follows:

$$f(x) = \left[N_R T_p \right] \quad (5)$$

$$N_R = \sum_{i=1}^{N_v} \alpha_i \quad (6)$$

$$\alpha = \begin{cases} \sum_{i=1}^{N_{vh}} \alpha_i & if\ TTL - TI = 0 \\ N_R & if\ TTL - TI > 0 \end{cases} \quad (7)$$

$$\alpha_i = V(N_R, P_{nc}, T_{wr}, TTL, TI, L_v) \quad (8)$$

Here, f(x) defines the fitness function that consists of retransmissions time (*NR*) and propagation time (*TP*) metrics values for optimization. Hence, lesser the value of *NR* and *TP* will be considered as the best fitness values.

Algorithm 2 Hybrid Genetic Firefly Algorithm-Based Routing Protocol (HGFA) Protocol

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Input:

  FF_i   Swarm size (Set of i firefly)
          where i = 1, 2, 3, ...N
  ω   parameter controlling the step size
  ξ   *Attractiveness of firefly*
  ψ   *Light absorption coefficient*
  FI   *Light intensity of firefly*
  r   *Distance between two firefly*
  Max   *Maximum no of iteration, i.e., {as per opted scenario}*

Output: Pareto optimal solution

$$\min_{V_N \in [LB_N, UB_N]_{N=1,2,3.....K}} f(V\_trans)$$
$$= \{V_1, V_2, V_3 \ldots \ldots \ldots V_K\}$$
$$QoS = \underset{i=1,2,3,....,I}{Maximize}(P_{V_i})$$

1. $f(Obj) = \underset{i=1,2,3,.....,I}{Minimize}(V\_trans_i)$
2. Sort firefly according to $f(Obj)$
3. for X← 1 to Max do
    for D← X to Y
        If $FI_i > FI_j$
          a) $FF_{i+1} = FF_i + \xi e^{-\psi r^2}(FF_j - FF_i) + \omega\left(rand - \dfrac{\mu}{\mu_k}\right)$
          b) update light intensity FI using a fitness function
          c) endif
    end for
4. generate new firefly position using GA
5. **End for**

As in VANET, the movement of vehicles is random with their speed and directions, so the stationary point distance is taken for the objective function. For two-dimensional distance, Cartesian distance is considered among the node points. The objective was to increase the objective function value at maximum. Therefore, the movement of vehicle nodes is made dynamically in respect to each other. The steps of the proposed algorithm are represented in Algorithm 2.

D. COMPUTATIONAL COMPLEXITY

The computational complexity of the proposed HGFA protocol is computing Big-Oh (O) asymptomatic notation. It lies for the set of "$1 < logn < \sqrt{n} < n < nlogn < n^2 < n^3 < \ldots < 2^n < 3^n < \ldots \ldots n^n$." Since the Big O is the upper bound of the function, therefore, function $f(n) = O(g(n))$ if $f \exists + ve$ constants c and number such that $f(n) \leq c * g(n) \forall n \geq n0$. Here, $f(n) \leq c * g(n)$, c is a constant. Thus, the computational complexity can be computed as:

$$C_t = O(cost_f * n) \tag{9}$$

Thus, the computational complexity of the proposed algorithm is $O(n^2)$.

IV. PERFORMANCE ANALYSIS

A. EXPERIMENTAL SET-UP

To simulate the proposed scenario NS3.26 an open-source network simulation tool is used. The setup is configured on Ubuntu Operating System with Core i5 and 8 GB RAM. Only open-source software tools are used to test the proposed methodology [26]. The parameters required for the experimental analysis are illustrated in Table 1.

TABLE 1. Simulation parameters.

Parameters	Value
Nodes	8,12,16,20,24,28,32,36,40,45,50
Fireflies	8,12,16,20,24,28,32,36,40,45,50
Maximum Speed	35 km/h
Minimum Speed	10 km/h
Number of data packets	10
Vehicle density	30 nodes/km
Jam density (blocked traffic)	50 nodes/km
Mobility Model	Manhattan Mobility Model
Antenna	Dual
Communication range	MIMO (250 m)
Spectrum scarcity	Cognitive radios
Vehicular range speed	(10-60) $kmph$
Pair	20 (default)
Packet size	512 bytes
MAC	IEEE 802.11 MAC (11 Mbps)
Propagation model	Nakagami Model
Simulation time	2000s
Data sending rate	2 Mbps
Routing agent	UDP/CBR

B. COMPARATIVE ANALYSIS

The simulation is performed randomly many times. The transmission time is calculated for various destination nodes based on source and destination nodes. To test these two different network scenarios are selected. The first is with lesser nodes to create a sparse network environment. This setup has a maximum of 50 nodes only. Then for the dense network environment maximum with 500 nodes. The same parameters and nodes were taken to simulate the test for pre-existing standard algorithms like the firefly algorithm and Particle Swarm Optimization using the same simulation standards. The parameters taken are maximum and minimum

speed as per the real traffic scenarios. A similar simulation procedure has given utmost results in another VANET network environment also [2]. The number of data packets is limited to 10 as it is a standard for a vehicle density of 30/km. The Manhattan communication mobility model is used for a generic city traffic simulation environment. The transmission time logs were recorded for comparison. The comparison of transmission time for three of these algorithms viz., proposed Hybrid Genetic Firefly Algorithm-based Routing Protocol (HGFA), standard firefly algorithm, and PSO algorithm illustrated in Figures 3 and 4.
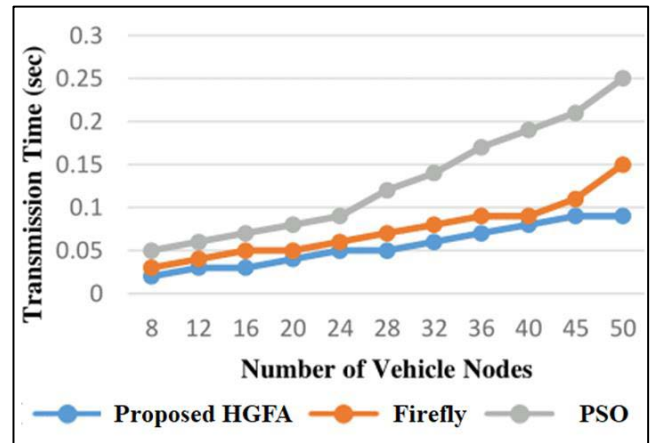

FIGURE 3. Comparative analysis of routing algorithm for transmission time in a sparse network scenario.
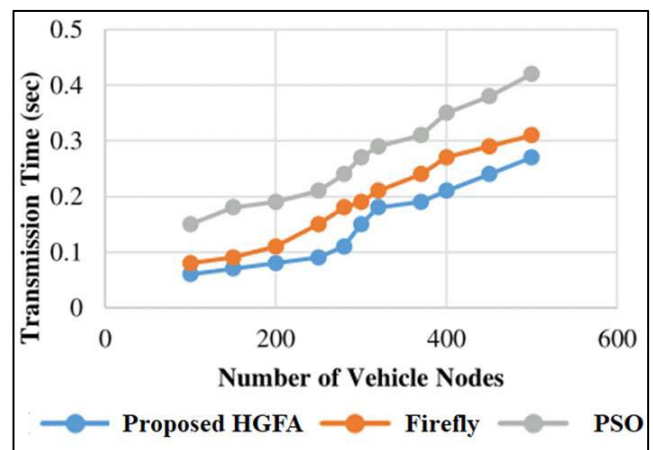

FIGURE 4. Comparative analysis of routing algorithm for transmission time in a dense network scenario.

From Figures 3 and 4, it is found that the performance of the proposed routing algorithm is better when compared with the standard routing algorithms of VANET, i.e., Firefly and PSO. The same test is also performed for other performance metrics like packet data delivery ratio and average throughput computed during simulation results. This has been found that for both the proposed approach HGFA has shown better results in comparison with the considered other routing protocols
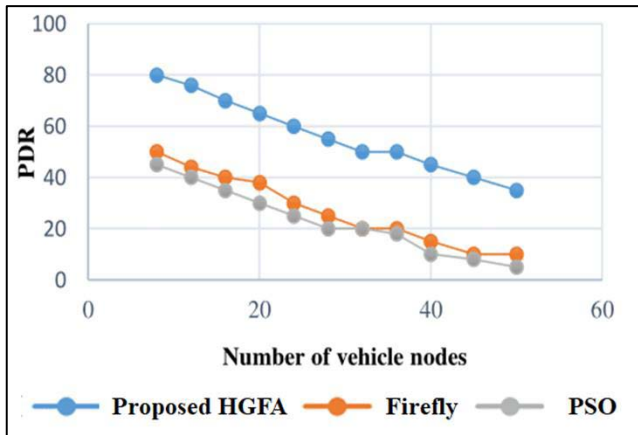
FIGURE 5. Comparative analysis of packet delivery ratio for a sparse network scenario.
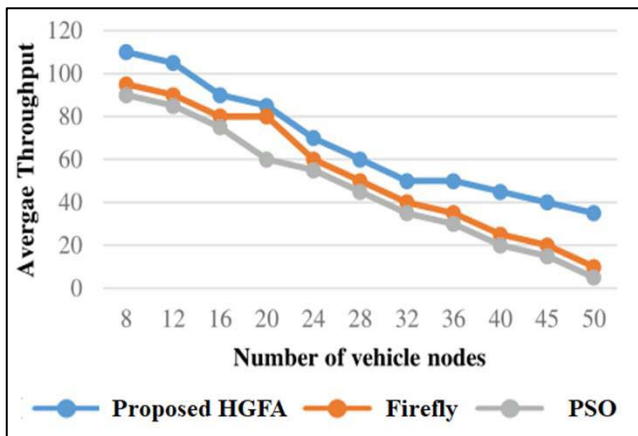

FIGURE 6. Comparative analysis of average throughput for a sparse network scenario.

Figures 5 and 6 represent the performance in the same traffic scenarios in terms of transmission time and packet delivery ratio, respectively. It is observed that compared to the competitive techniques the proposed protocol achieves significantly lesser transmission time.

Further, to validate the performance in comparison with the proposed technique other traditional non-swarm-based protocols have also been tested. The same simulation environment and parameters are taken for similarity. The next phase was to test it for AODV and OLSR in proposed simulation environments. Though it is found that these routing protocols are the standard routing protocols used in VANET and they have their distinctive properties in VANET for dense, sparse, and real city traffic network scenarios. The test was performed to gather the logs for the transmission time of data packets for each routing protocol. The comparison of transmission time for three of these algorithms viz., proposed HGFA algorithm, AODV and OLSR are illustrated in Tables 2 and 3 for dense and sparse network scenarios, respectively. It is found that the transmission time is minimum in the proposed algorithm while AODV also performed better in comparison with OLSR.

TABLE 2. Transmission time computed from standard AODV and OLSR routing protocol in dense network scenario with respect to proposed algorithm.

Destination Nodes	Proposed HGFA	AODV	OLSR
100	0.06	0.11	0.19
150	0.07	0.15	0.21
200	0.08	0.18	0.24
250	0.09	0.19	0.27
280	0.11	0.21	0.29
300	0.15	0.24	0.31
320	0.18	0.27	0.35
370	0.19	0.29	0.38
400	0.21	0.31	0.42
450	0.24	0.35	0.46
500	0.27	0.38	0.49

TABLE 3. Transmission time computed from standard AODV and OLSR routing protocol in a sparse network scenario with respect to proposed algorithm.

Destination Nodes	Proposed HGFA	AODV	OLSR
8	0.02	0.05	0.12
12	0.03	0.06	0.14
16	0.03	0.07	0.15
20	0.04	0.08	0.18
24	0.05	0.09	0.22
28	0.05	0.09	0.24
32	0.06	0.12	0.28
36	0.07	0.14	0.32
40	0.08	0.15	0.34
45	0.09	0.18	0.37
50	0.09	0.22	0.39

C. DISCUSSION

In [2], the authors illustrated the performance significance of ACO in comparison with their proposed hybrid algorithm for sparse network scenarios. But they have not tested it for AODV, OLSR, Firefly, and PSO techniques. Their results are shown in Table 4 which shows that integration of the GA approach has benefitted the ACO performance. Similarly, this research represents that the proposed HGFA is performing better in different traffic network environments. For its robustness and versatility, it is also compared with four different types of routing algorithms. The performance significance statistics are shown for HGFA in comparison with Firefly, PSO, AODV, and OLSR traditional VANET routing protocols in Table 5. This shows that the proposed HGFA protocol

TABLE 4. Performance significance comparison done earlier [2].

Routing Algorithm	Dense Network	Sparse Network
PDR GAACO with ACO	1.7%	1.5%
Average Throughput GAACO with ACO	1.2%	1.3%

TABLE 5. Performance significance comparison with respect to traditional algorithms.

Routing Algorithm	Dense Network	Sparse Network
HGFA with DSDV	0.77%	0.74%
HGFA with PSO	0.55%	0.42%
HGFA with AODV	0.62%	0.49%
HGFA with OLSR	0.46%	0.23%

TABLE 6. Comparative analysis among the proposed and the competitive protocols on both sparse and dense scenarios.

Scenario	Sparse network		Dense network	
Protocol	PDR	Transmission time	PDR	Transmission time
AODV [28]	28	0.175	21	0.282
DSDV	29	0.169	19	0.318
OLSR [28]	27	0.181	23	0.263
GAACO [2]	34	0.130	31	0.216
CORA [29]	34	0.148	29	0.192
GAACO-PSO [2]	32	0.136	27	0.227
CBLTR [29]	31	0.124	29	0.234
IDVR [29]	32	0.129	33	0.197
PFQ-AODV [27]	37	0.107	34	0.219
ZRP [28]	33	0.132	29	0.238
GBSR-B [30]	35	0.148	33	0.197
Proposed GAFF	**41**	**0.095**	**37**	**0.154**

performs significantly better in respect to transmission time at two different traffic environments, i.e., dense traffic network scenario and sparse traffic network scenario

Table 6 shows the comparative analysis among the proposed GAFF and the competitive routing protocols for both sparse and dense networks. For sparse and dense networks, we have considered 50 and 300 nodes, respectively. It is found that the proposed protocol outperforms the competitive protocols in terms of PDR and transmission time by 4.78% and 1.92%, respectively for sparse networks. Also, for dense networks, the proposed protocol outperforms the competitive protocols in terms of PDR and transmission time by 3.92% and 1.76%, respectively. Therefore, the proposed protocol is effective for both sparse and dense networks.

V. CONCLUSION
In this paper, an efficient routing protocol was proposed by using the firefly algorithm with the GA technique. The proposed methodology has utilized the nature of fireflies to complete the task and coordinate with other nodes. The distinctive features of GA were applied to design a new objective function for the proposed algorithm. Proposed HGFA was tested and compared with the standard Firefly and PSO

routing algorithm. The data gathered through the simulation result validates that the transmission was reduced significantly when was applied for sparse and dense traffic networks and performed even better for the other two performance metrics such as PDR and average throughput. Comparative analysis have revealed that the developed approach has shown better performance in transmission time with 0.77% and 0.55% of significance in dense network scenarios and 0.74% and 0.42 % in a sparse network scenario in comparison with the existing VANET routing algorithms such as standard Firefly and PSO. The resultant comparison for two basic VANET routing protocols like AODV and OLSR with HGFA shows significant improvement of 0.62% and 0.46% in the dense network whereas 0.49% and 0.23% in sparse network scenarios. It was also found that the proposed protocol outperforms the competitive protocols in terms of PDR and transmission time by 4.78% and 1.92%, respectively for sparse networks. Also, for dense networks, the proposed protocol outperforms the competitive protocols in terms of PDR and transmission time by 3.92% and 1.76%, respectively. Hence, this concludes that the proposed algorithm is better and can be further deployed for research and implementation of Swarm Intelligence-based routing algorithm in VANET.

REFERENCES

[1] J. Luo and J. P. Hubaux, "A survey of research in inter-vehicle communications," in *Embedded Security in Cars: Securing Current and Future Automotive IT Applications*. Berlin, Germany: Springer, 2006, pp. 111–122.

[2] G. D. Singh, M. Prateek, and G. H. Sastry, "Swarm intelligence based efficient routing algorithm for platooning in VANET through ant colony optimization," *Int. J. Innov. Technol. Explor. Eng.*, vol. 8, no. 9, pp. 1238–1244, 2019, doi: 10.35940/ijitee.i7888.078919.

[3] R. Sadakale, N. V. K. Ramesh, and R. Patil, "TAD-HOC routing protocol for efficient VANET and infrastructure-oriented communication network," *J. Eng.*, vol. 2020, pp. 1–12, Jul. 2020, doi: 10.1155/2020/8505280.

[4] A. Guillen-Perez, A.-M. Montoya, J.-C. Sanchez-Aarnoutse, and M.-D. Cano, "A comparative performance evaluation of routing protocols for flying ad-hoc networks in real conditions," *Appl. Sci.*, vol. 11, no. 10, p. 4363, May 2021, doi: 10.3390/APP11104363.

[5] P. Kumar Singh, K. Lego, and D. T. Tuithung, "Simulation based analysis of adhoc routing protocol in urban and highway scenario of VANET," *Int. J. Comput. Appl.*, vol. 12, no. 10, pp. 42–49, Dec. 2011, doi: 10.5120/1716-2302.

[6] F. S. Mubarek, F. S. Mubarek, S. A. Aliesawi, K. M. A. Alheeti, and N. M. Alfahad, "Urban-AODV: An improved AODV protocol for vehicular ad-hoc networks in urban environment," *Int. J. Eng. Technol.*, vol. 7, no. 4, pp. 3030–3036, Sep. 2018, doi: 10.14419/ijet.v7i4.21535.

[7] G. D. Singh, M. Prateek, and H. S. G, "Swarm intelligence based algorithm for efficient routing in VANET," *Int. J. Innov. Technol. Explor. Eng.*, vol. 9, no. 5, pp. 1124–1136, 2020, doi: 10.35940/ijitee.e2857.039520.

[8] R. Sugumar, A. Rengarajan, and C. Jayakumar, "Trust based authentication technique for cluster based vehicular ad hoc networks (VANET)," *Wireless Netw.*, vol. 24, no. 2, pp. 373–382, Jul. 2016, doi: 10.1007/S11276-016-1336-6.

[9] S. Allal and S. Boudjit, "Geocast routing protocols for VANETs: Survey and guidelines," in *Proc. 6th Int. Conf. Innov. Mobile Internet Services Ubiquitous Comput.*, Jul. 2012, pp. 323–328, doi: 10.1109/IMIS.2012.133.

[10] K. Khalid, I. Woungang, S. K. Dhurandher, and J. Singh, "Energy-efficient fuzzy geocast routing protocol for opportunistic networks," in *Proc. Int. Conf. Adv. Inf. Netw. Appl.*, in Lecture Notes in Networks and Systems, vol. 225, May 2021, pp. 553–565, doi: 10.1007/978-3-030-75100-5_48.

[11] D. Jiang, G. Hu, G. Qi, and N. Mazur, "A fully convolutional neural network-based regression approach for effective chemical composition analysis using near-infrared spectroscopy in cloud," *J. Artif. Intell. Technol.*, vol. 1, no. 1, pp. 74–82, Jan. 2021.

[12] H. S. Basavegowda and G. Dagnew, "Deep learning approach for microarray cancer data classification," *CAAI Trans. Intell. Technol.*, vol. 5, no. 1, pp. 22–33, Mar. 2020.

[13] Y. Xu and T. T. Qiu, "Human activity recognition and embedded application based on convolutional neural network," *J. Artif. Intell. Technol.*, vol. 1, no. 1, pp. 51–60, Dec. 2020.

[14] S. Ghosh, P. Shivakumara, P. Roy, U. Pal, and T. Lu, "Graphology based handwritten character analysis for human behaviour identification," *CAAI Trans. Intell. Technol.*, vol. 5, no. 1, pp. 55–65, Mar. 2020.

[15] G. Hu, S.-H.-K. Chen, and N. Mazur, "Deep neural network-based speaker-aware information logging (SAIL) for augmentative and alternative communication," *J. Artif. Intell. Technol.*, vol. 1, no. 2, pp. 138–143, Apr. 2021.

[16] M. Fahad, F. Aadil, S. Khan, P. A. Shah, K. Muhammad, J. Lloret, H. Wang, J. W. Lee, and I. Mehmood, "Grey wolf optimization based clustering algorithm for vehicular ad-hoc networks," *Comput. Electr. Eng.*, vol. 70, pp. 853–870, Aug. 2018, doi: 10.1016/j.compeleceng.2018.01.002.

[17] M. Chahal and S. Harit, "Optimal path for data dissemination in vehicular ad hoc networks using meta-heuristic," *Comput. Electr. Eng.*, vol. 76, pp. 40–55, Jun. 2019, doi: 10.1016/j.compeleceng.2019.03.006.

[18] H. Bello-Salau, A. M. Aibinu, Z. Wang, A. J. Onumanyi, E. N. Onwuka, and J. J. Dukiya, "An optimized routing algorithm for vehicle ad-hoc networks," *Eng. Sci. Technol., Int. J.*, vol. 22, no. 3, pp. 754–766, Jun. 2019, doi: 10.1016/j.jestch.2019.01.016.

[19] C. J. Joshua, R. Duraisamy, and V. Varadarajan, "A reputation based weighted clustering protocol in VANET: A multi-objective firefly approach," *Mobile Netw. Appl.*, vol. 24, no. 4, pp. 1199–1209, Aug. 2019, doi: 10.1007/s11036-019-01257-z.

[20] M. A. Mohammed, M. K. A. Ghani, R. I. Hamed, S. A. Mostafa, M. S. Ahmad, and D. A. Ibrahim, "Solving vehicle routing problem by using improved genetic algorithm for optimal solution," *J. Comput. Sci.*, vol. 21, pp. 255–262, Jul. 2017, doi: 10.1016/j.jocs.2017.04.003.

[21] B. Gupta, M. Tiwari, and S. S. Lamba, "Visibility improvement and mass segmentation of mammogram images using quantile separated histogram equalisation with local contrast enhancement," *CAAI Trans. Intell. Technol.*, vol. 4, no. 2, pp. 73–79, Jun. 2019.

[22] M. Elhoseny, "Intelligent firefly-based algorithm with Levy distribution (FF-L) for multicast routing in vehicular communications," *Expert Syst. Appl.*, vol. 140, Feb. 2020, Art. no. 112889, doi: 10.1016/j.eswa.2019.112889.

[23] A. Galvez and A. Iglesias, "Firefly algorithm for Bezier curve approximation," in *Proc. 13th Int. Conf. Comput. Sci. Appl.*, Jun. 2013, pp. 81–88, doi: 10.1109/ICCSA.2013.21.

[24] J. J. Rubio, C. L. Vidal-Silva, R. Soto, E. Madariaga, F. Johnson, and L. Carter. (2019). *Applying FireFly Algorithm to Solve the Problem of Balancing Curricula*. Accessed: Apr. 8, 2021. [Online]. Available: https://thesai.org/Publications/IJACSA

[25] M. Jafer, M. A. Khan, S. U. Rehman, and T. A. Zia, "Optimizing broadcasting scheme for VANETs using genetic algorithm," in *Proc. IEEE 41st Conf. Local Comput. Netw. Workshops (LCN Workshops)*, Nov. 2016, pp. 222–229, doi: 10.1109/LCN.2016.051.

[26] G. D. Singh, M. Prateek, and G. H. Sastry, "Methodology to perform simulation experiments for realistic VANET scenarios using open source software tools," *Int. J. Psychosoc. Rehabil.*, vol. 24, no. 6, pp. 10170–10175, 2020.

[27] C. Wu, S. Ohzahata, and T. Kato, "Flexible, portable, and practicable solution for routing in VANETs: A fuzzy constraint Q-learning approach," *IEEE Trans. Veh. Technol.*, vol. 62, no. 9, pp. 4251–4263, Nov. 2013.

[28] J. J. Ferronato and M. A. S. Trentin, "Analysis of routing protocols OLSR, AODV and ZRP in real urban vehicular scenario with density variation," *IEEE Latin Amer. Trans.*, vol. 15, no. 9, pp. 1727–1734, Aug. 2017.

[29] A. Abuashour and M. Kadoch, "Performance improvement of cluster-based routing protocol in VANET," *IEEE Access*, vol. 5, pp. 15354–15371, 2017.

[30] C. T. Barba, L. U. Aguiar, and M. A. Igartua, "Design and evaluation of GBSR-B, an improvement of GPSR for VANETs," *IEEE Latin Amer. Trans.*, vol. 11, no. 4, pp. 1083–1089, Jun. 2013.

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